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OBLON, SPIVAK, MCCLELLAND MAIER & NEUSTADT, P.C.
1940 DUKE STREET
ALEXANDRIA, VA 22314

EXAMINER	
PARK, EDWARD	

ART UNIT	PAPER NUMBER
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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Notice of the Office communication was sent electronically on above-indicated "Notification Date" to the following e-mail address(es):

patentdocket@oblon.com
oblonpat@oblon.com
jgardner@oblon.com

Office Action Summary	Application No.	Applicant(s)	
	10/517,615	SUZUKI ET AL.	
	Examiner	Art Unit	
	EDWARD PARK	2624	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE *3* MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *05 December 2008*.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-23* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-4,8,11-13 and 16-22* is/are rejected.

7)☒ Claim(s) *5-7,9-10,14-15,23* is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☐ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date _____.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

DETAILED ACTION

Continued Examination Under 37 CFR 1.114

1. A request for continued examination under 37 CFR 1.114, including the fee set forth in 37 CFR 1.17(e), was filed in this application after final rejection. Since this application is eligible for continued examination under 37 CFR 1.114, and the fee set forth in 37 CFR 1.17(e) has been timely paid, the finality of the previous Office action has been withdrawn pursuant to 37 CFR 1.114. Applicant's submission filed on 12/5/08 has been entered.

Specification

2. In response to applicant's amendment of the title on 6/3/08, the previous title objection is withdrawn.

Claim Rejections - 35 USC § 101

3. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

Claims 16, 17 are rejected under 35 U.S.C. 101 as not falling within one of the four statutory categories of invention. The Federal Circuit[1], relying upon Supreme Court precedent[2], has indicated that a statutory "process" under 35 U.S.C. 101 must (1) be tied to a particular machine or apparatus, or (2) transform a particular article to a different state or thing. This is referred to as the "machine or transformation test", whereby the recitation of a particular

[1] *In re Bilski*, 88 USPQ2d 1385 (Fed. Cir. 2008).

[2] *Diamond v. Diehr*, 450 U.S. 175, 184 (1981); *Parker v. Flook*, 437 U.S. 584, 588 n.9 (1978); *Gottschalk v. Benson*, 409 U.S. 63, 70 (1972); *Cochrane v. Deener*, 94 U.S. 780, 787-88 (1876).

machine or transformation of an article must impose meaningful limits on the claim's scope to impart patent-eligibility (See *Benson*, 409 U.S. at 71-72), and the involvement of the machine or transformation in the claimed process must not merely be insignificant extra-solution activity (See *Flook*, 437 U.S. at 590"). While the instant claim(s) recite a series of steps or acts to be performed, the claim(s) neither transform an article nor are positively tied to a particular machine that accomplishes the claimed method steps, and therefore do not qualify as a statutory process. That is, the method includes steps of extracting, retaining, comparing, detecting, etc. is of sufficient breadth that it would be reasonably interpreted as a series of steps completely performed mentally, verbally, or without a machine. The cited claims do not positively recite any structure within the body of the claim which ties the claim to a statutory category. Furthermore, the examiner suggests that the structure needs to tie in the basic inventive concept of the application to a statutory category. Structure that ties insignificant pre or post solution activity to a statutory category is not sufficient in overcoming the 101 issue.

[1] *In re Bilski*, 88 USPQ2d 1385 (Fed. Cir. 2008).

[2] *Diamond v. Diehr*, 450 U.S. 175, 184 (1981); *Parker v. Flook*, 437 U.S. 584, 588 n.9 (1978); *Gottschalk v. Benson*, 409 U.S. 63, 70 (1972); *Cochrane v. Deener*, 94 U.S. 780, 787-88 (1876).

Claim Rejections - 35 USC § 103

4. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

5. **Claims 1-4, 8, 16, 20** are rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Hull (US 5,832,110).

Regarding **claim 1**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the method comprising:

feature point extracting method for extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2 , interest points are local features with high information content … database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images)

feature quantity retention method for extracting and retaining each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

feature quantity comparison method for comparing the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query

image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive). Schmid does not disclose feature quantity retention means for extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; and if any, wherein the feature quantity comparison method itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms. While Schmid discloses these steps, Schmid does not disclose an apparatus implementing these steps.

Roehrig, in the same field of endeavor, teaches feature quantity retention means for extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point

or region, a histogram of gradient directions is centered around the candidate point) and an apparatus implementing these steps (see fig. 1b).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair and an apparatus as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59) and to provide the ability to isolate and extract model images to be disseminated and used by the millions of people who have access to computers.

Hull, in the same field of endeavor, teaches if any, wherein the feature quantity comparison method itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms (see fig. 1, fig. 2, col. 2, lines 15-40; a horizontal projection histogram is calculated from a first image fragment and compared to a horizontal histogram from a second image fragment. By manipulating the two histograms until they are "aligned," the rotation (.theta.) and vertical translation (y) parameters of the transformation are determined. Knowing these two parameters, the horizontal translation (x) parameter is easily calculated by sliding the image fragments relative to each other horizontally. In one variation, vertical histograms are used to determine the rotation and horizontal translation first. Because the histograms are being manipulated and not the entire image fragments, much less computational effort and memory are needed to perform image registration. Instead of

rotating an image to determine the transformation's angle of rotation, the histograms are transformed according to a "histogram rotation" transformation).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig to utilize shifting of feature points as taught by Hull, to reduce computation costs and memory cost by overcoming the need to store the entire images while the feature points are calculated (see col. 1, lines 45-65).

Regarding **claims 2-4**, Schmid further discloses extracts and retains, as the feature quantity, an average density gradient vector for each of plurality of partial regions into which the neighboring region is further divided (see section 3.1, V represent the average luminance), and the feature quantity comparison means generates the candidate-associated feature point pair based on a distance between density gradient direction histograms for the feature points to be compared and on similarity between feature vectors which are collected in the neighboring region as average density gradient vectors in each of the partial regions (see section 4.2, 4.2.1, 4.3, 4.4 semilocal constraints are utilized so there is no miss-detection of points which has the p closest features are selected which therefore transforms the vector T(k) which is determined by the distance threshold t according to the X^2 distribution);

generates a provisional candidate-associated feature point pair based on a distance between the density gradient direction histograms for the feature points to be compared and, based on the similarity between feature vectors, selects the candidate-associated feature point pair from the provisional candidate-associated feature point pair (see section 4.2, 4.3 essentially the provisional candidate implies repeating the process which is evident in any algorithm);

using a rotation angle equivalent to a shift a amount giving the shortest distance to correct a density gradient direction of a density gradient vector in the neighboring region and selects the candidate-associated feature point pair from the provisional candidate-associated feature point pair based on similarity between the feature vectors in a corrected neighboring region (see figures 4, 5, section 4.3 geometric constraint is added based on the angel between neighbor points).

Regarding **claim 8**, Schmid further discloses candidate-associated feature point pair selection means for creating a rotation angle histogram concerning a rotation angle equivalent to a shift amount giving the shortest distance and selects a candidate-associated feature point pair giving a rotation angle for a peak in the rotation angle histogram from the candidate-associated feature point pair generated by the feature quantity comparison means (see figures 4, 5, section 4.3 geometric constraint is added based on the angel between neighbor points), wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

Regarding **claim 16**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the method comprising:

extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared) extracting and retaining each of the object image and the model image (see section 2, 4.4); comparing the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and
detecting the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive). Schmid does not disclose extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; and if any, wherein the comparing itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated

feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Hull, in the same field of endeavor, teaches if any, wherein the comparing itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms (see fig. 1, fig. 2, col. 2, lines 15-40; a horizontal projection histogram is calculated from a first image fragment and compared to a horizontal histogram from a second image fragment. By manipulating the two histograms until they are "aligned," the rotation (.theta.) and vertical translation (y) parameters of the transformation are determined. Knowing these two parameters, the horizontal translation (x) parameter is easily calculated by sliding the image fragments relative to each other horizontally. In one variation, vertical

histograms are used to determine the rotation and horizontal translation first. Because the histograms are being manipulated and not the entire image fragments, much less computational effort and memory are needed to perform image registration. Instead of rotating an image to determine the transformation's angle of rotation, the histograms are transformed according to a "histogram rotation" transformation).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig to utilize shifting of feature points as taught by Hull, to reduce computation costs and memory cost by overcoming the need to store the entire images while the feature points are calculated (see col. 1, lines 45-65).

Regarding **claim 20**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the method comprising:

a feature point extracting method configure to extract a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, interest points are local features with high information content ... database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images)

a feature quantity retention method configured to extract and retain each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most

similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

a feature quantity comparison method configured to compare the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

a model attitude estimation method configured to detect the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive). Schmid does not disclose extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; and if any, wherein the feature quantity comparison method itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms. While Schmid discloses these steps, Schmid does not disclose an apparatus implementing these steps.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point) and an apparatus implementing these steps (see fig. 1b).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair and an apparatus as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59) and to provide the ability to isolate and extract model images to be disseminated and used by the millions of people who have access to computers.

Hull, in the same field of endeavor, teaches if any, wherein the feature quantity comparison method itinerantly shifts one of the feature points to be compared to find distances and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms (see fig. 1, fig. 2, col. 2, lines 15-40; a horizontal projection histogram is calculated from a first image fragment and compared to a horizontal histogram from a second image fragment. By manipulating the two histograms until they are "aligned," the rotation (.theta.) and vertical translation (y) parameters of the transformation are determined. Knowing these two parameters, the horizontal translation (x)

parameter is easily calculated by sliding the image fragments relative to each other horizontally. In one variation, vertical histograms are used to determine the rotation and horizontal translation first. Because the histograms are being manipulated and not the entire image fragments, much less computational effort and memory are needed to perform image registration. Instead of rotating an image to determine the transformation's angle of rotation, the histograms are transformed according to a "histogram rotation" transformation).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig to utilize shifting of feature points as taught by Hull, to reduce computation costs and memory cost by overcoming the need to store the entire images while the feature points are calculated (see col. 1, lines 45-65).

6. **Claims 11-13, 21, 22** are rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE), Roehrig et al (US 5,815,591) with Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision), and further in view of Matsuzaki et al (US 6,804,683 B1).

Regarding **claims 11-13**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the apparatus comprising:

a feature point extracting step of extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, interest points are local features with high information content … database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images)

a feature quantity retention step of extracting and retaining each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

a feature quantity comparison step of comparing the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image, that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k));

a model attitude estimation step of detecting the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

Schmid does not teach extracting and retaining a feature quantity in a neighboring region at the feature point, the feature quantity being a density direction histogram storing an umber of points near the feature point having each of a plurality of gradient directions, projecting an affine

transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space, a centroid for the cluster having the largest number of members to be an affine transformation parameter to determine a position and an attitude of the model, and a least squares estimation to find an affine transformation parameter for determining a position and attitude of the model.

Roehrig, in the same field of endeavor, teaches extracting and retaining a feature quantity in a neighboring region at the feature point, the feature quantity being a density direction histogram storing an umber of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and

finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters … select key locations at maxima and minima of a difference of Gaussian function applied in scale space) and a centroid for the cluster having the largest number of members to be an affine transformation parameter to determine a position and an attitude of the model (see section 5, cluster reliable model hypotheses is to use the Hough transform to search for keys that agree upon a particular model pose where each model key in the database contains a record of the key's parameters relative to the model coordinate system and therefore can predict the model location), and a least squares estimation to find an affine transformation parameter for determining a position and attitude of the model (see section 1, collection of keys that agree on a potential model pose are identified and then through a least-squares fit to a final estimate of model parameters).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig combination to utilize affine transformation parameter with centroid and least squares estimation as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

While Schmid discloses these steps, Schmid does not disclose an apparatus implementing these steps.

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps (see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the steps of Schmid, Roehrig with Lowe combination to utilize an apparatus as taught by Matsuzami, in order to ensure a high computational speed, and to provide the ability to isolate and extract model images to be disseminated and used by the millions of people who have access to computers.

Regarding **claim 21**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the method comprising:

a feature point extracting step configured to extract a feature point from each of the object image and the model image (see section 1.2, 2, 4.2 , interest points are local features with high information content … database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images)

a feature quantity retention step configured to extract and retain each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

a feature quantity comparison step configured to compare the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and to generate a candidate-associated feature point pair having similar feature quantities, each

feature quantity not including gradient magnitude information (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k));
a model attitude estimation step configured to detect the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

Schmid does not teach extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions

(see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters … select key locations at maxima and minima of a difference of Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig combination to utilize affine transformation parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

While Schmid discloses these steps, Schmid does not disclose an apparatus implementing these steps.

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps (see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the steps of Schmid, Roehrig with Lowe combination to utilize an apparatus as taught by Matsuzami, in order to ensure a high computational speed, and to provide the ability to isolate and extract model images to be disseminated and used by the millions of people who have access to computers.

Regarding **claim 22**, Schmid discloses generating each candidate-associated feature point pair to include one feature point of the object image and one feature point of the model image with a dissimilarity less than a threshold (see section 4.2, 4.2.1).

7. **Claim 17** is rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision).

Regarding **claim 17**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the apparatus comprising:
extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is

added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared) extracting and retaining each of the object image and the model image (see figure 3, section 4.2, 4.2.1, 4.2.2, voting algorithm which is a sum of the number of times each model is selected which produces a histogram that correctly identifies the model images from the database of images);

comparing the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

detecting the presence or absence of the model on the object image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

Schmid does not teach extracting and retaining a feature quantity in a neighboring region a the feature point, the feature quantity being a density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine

transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space.

Roehrig, in the same field of endeavor, teaches extracting and retaining a feature quantity in a neighboring region a the feature point, the feature quantity being a density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine

transformation parameters … select key locations at maxima and minima of a difference of Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig combination to utilize affine transformation parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

8. **Claim 18** is rejected under 35 U.S.C. 103(a) as being unpatentable over Watanabe et al (US 7,084,900 B1), Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Hull (US 5,832,110).

Regarding **claim 18**, Watanabe discloses an autonomous robot apparatus (figure 1, col. 2, lines 37-60, wrist of a robot RB that is included in the robot system) capable of comparing an input image with a model image containing a model to be detected and extracting the model from the input image, the apparatus comprising:

image input means for imaging an outside environment to generate the input image (figure 1, numeral 20; col. 2, lines 37-60, image capturing device (camera or visual sensor) that captures an image of a stack of workpieces); and a processor (figure 3, numeral 1; col. 3, lines 3-10, robot operation programs that are performed by the processor).

Watanabe does not disclose a feature point extracting method for extracting a feature point from each of the input image and the model image;

feature quantity retention method for extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point in each of the input image and the model image, the

density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions;

feature quantity comparison method for comparing the feature quantity of each feature point of the input image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities; and

model attitude estimation method for detecting the presence or absence of the model on the input image using the candidate-associated feature point pair and estimating a position and an attitude of the model, if any, wherein the feature quantity comparison method itinerantly shifts one of the density gradient direction histograms of feature points to be compared in density gradient direction to find distances between the density gradient direction histograms and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms.

Schmid, in the same field of endeavor, teaches a feature point extracting method for extracting a feature point from each of the input image and the model image (see section 1.2, 2, 4.2 , interest points are local features with high information content … database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images);

feature quantity retention method for extracting and retaining, as a feature quantity, each of the input image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the

model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

feature quantity comparison method for comparing each feature point of the input image with each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the input image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the Watanabe reference to utilize feature point extracting, feature quantity retention, feature quantity comparison, model attitude estimation as taught by Schmid, in order to increase the reliability of the robot to track and retrieve targeted objects by improving the tracking ability of objects even if the image of the targeted object is "take from different viewpoints" or "only [a] part of [the] image is given" (see section 5.2.2.3, 5.2.2.4).

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram

storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Watanabe with Schmid combination to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Hull, in the same field of endeavor, teaches if any, wherein the feature quantity comparison method itinerantly shifts one of the density gradient direction histograms of feature points to be compared in density gradient direction to find distances between the density gradient direction histograms and generates the candidate-associated feature point pair by assuming a shortest distance to be a distance between the density gradient direction histograms (see fig. 1, fig. 2, col. 2, lines 15-40; a horizontal projection histogram is calculated from a first image fragment and compared to a horizontal histogram from a second image fragment. By manipulating the two histograms until they are "aligned," the rotation (.theta.) and vertical translation (y) parameters of the transformation are determined. Knowing these two parameters, the horizontal translation (x) parameter is easily calculated by sliding the image fragments relative to each other horizontally. In one variation, vertical histograms are used to determine the rotation and horizontal translation first. Because the histograms are being manipulated and not the entire image fragments, much less computational effort and memory are needed to perform

image registration. Instead of rotating an image to determine the transformation's angle of rotation, the histograms are transformed according to a "histogram rotation" transformation).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Watanabe, Schmid with Roehrig to utilize shifting of feature points as taught by Hull, to reduce computation costs and memory cost by overcoming the need to store the entire images while the feature points are calculated (see col. 1, lines 45-65).

9. **Claim 19** is rejected under 35 U.S.C. 103(a) as being unpatentable over Watanabe et al (US 7,084,900 B1), Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision).

Regarding **claim 19**, Watanabe discloses an autonomous robot apparatus (figure 1, col. 2, lines 37-60, wrist of a robot RB that is included in the robot system) capable of comparing an input image with a model image containing a model to be detected and extracting the model from the input image, the apparatus comprising:

image input means for imaging an outside environment to generate the input image (figure 1, numeral 20; col. 2, lines 37-60, image capturing device (camera or visual sensor) that captures an image of a stack of workpieces); and a processor (figure 3, numeral 1; col. 3, lines 3-10, robot operation programs that are performed by the processor).

Watanabe does not disclose a feature point extracting method for extracting a feature point from each of the input image and the model image;

feature quantity retention method for extracting and retaining a feature quantity in a neighboring region at the feature point in each of the input image and the model image, the

feature quantity being a density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions;

feature quantity comparison method for comparing the feature quantity of each feature point of the input image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities; and a model attitude estimation method for detecting the presence or absence of the model on the input image using the candidate-associated feature point pair and estimating a position and an attitude of the model, if any, wherein the model attitude estimation means repeatedly projects an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space.

Schmid, in the same field of endeavor, teaches a feature point extracting method for extracting a feature point from each of the input image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared); feature quantity retention method for extracting and retaining each of the input image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is

defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

feature quantity comparison method for comparing the feature quantity of each feature point of the input image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the input image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the Watanabe reference to utilize feature point extracting, feature quantity retention, feature quantity comparison, model attitude estimation as taught by Schmid, in order to increase the reliability of the robot to track and retrieve targeted objects by improving the

tracking ability of objects even if the image of the targeted object is "take from different viewpoints" or "only [a] part of [the] image is given" (see section 5.2.2.3, 5.2.2.4).

Roehrig, in the same field of endeavor, teaches extracting and retaining as a feature quantity in a neighboring region at the feature point, the feature quantity being a density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Watanabe with Schmid combination to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters … select key locations at maxima and minima of a difference of Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Watanabe, Schmid, with Roehrig combination to utilize affine transformation parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

Allowable Subject Matter

10. Claims 5, 6, 7, 9, 10, 14, 15, 23 are objected to as being dependent upon a rejected base claim, but would be allowable if rewritten in independent form including all of the limitations of the base claim and any intervening claims.

Regarding claims 5-7, none of the references of record alone or in combination suggest or fairly teach wherein the model attitude estimation means repeatedly projects an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space, wherein the model attitude estimation means assumes a centroid for the cluster having the largest number of members to be an affine transformation parameter to determine a position and an attitude of the model, and wherein the model attitude estimation means assumes a candidate-associated feature point pair giving the affine transformation parameter belonging to a cluster having the largest number of members to be a true candidate-associated feature point pair and uses the true candidate associated feature point pair for a least squares estimation to find an affine transformation parameter for determining a position and attitude of the model.

Regarding claims 9, 10, none of the references of record alone or in combination suggest or fairly teach candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature quantity comparison means,
wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any; and wherein the feature point extraction means extracts a local maximum point or a local minimum point in second-order differential filter output images with respective resolutions as the feature point, i.e., a point free from positional changes due to resolution changes within a specified range in a multi-resolution pyramid structure acquired by repeatedly applying smoothing filtering and reduction resampling to the object image or the model image.

Regarding claims 14, 15, none of the references of record alone or in combination suggest or fairly teach candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature quantity comparison means,

wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any; and wherein the feature point extraction means extracts a local maximum point or a local minimum point in second-order differential filter output images with respective resolutions as the feature point, i.e., a point free from positional changes due to resolution changes within a specified range in a multi-resolution pyramid structure acquired by repeatedly applying smoothing filtering and reduction resampling to the object image or the model image.

Regarding claim 23, none of the references of record alone or in combination suggest or fairly teach wherein the feature quantity comparison unit is configured to generate the dissimilarity for each respective candidate-associated feature point pair by itinerantly shifting by one step the plurality of gradient directions for one of the object image and the model image to compute a number of similarities to a number of the plurality of gradient directions, and to take a minimum dissimilarity to be the dissimilarity.

Response to Arguments

11. Applicant's arguments with respect to claim 16 have been considered but are moot in view of the new ground(s) of rejection. Applicant argues that the Schmid reference does not disclose the cited limitation "itinerantly shifting …." as seen in the argument section (see pg. 15, second paragraph – pg. 17, second paragraph). This argument is not considered persuasive since

claim 16 is rejected by a new ground(s) of rejection under Schmid, with Roehrig and further in view of Hull and can be seen above in the rejection of the claim.

Applicant's arguments with respect to claim 1 have been considered but are moot in view of the new ground(s) of rejection. Applicant argues that the Schmid reference does not disclose the cited limitation "the feature quantity comparison means itinerantly shifts …." as seen in the argument section (see pg. 17, fourth paragraph – pg. 17, fifth paragraph). This argument is not considered persuasive since claim 1 is rejected by a new ground(s) of rejection under Schmid, with Roehrig and further in view of Hull and can be seen above in the rejection of the claim.

Applicant's arguments with respect to claim 20 have been considered but are moot in view of the new ground(s) of rejection. Applicant argues that the Schmid reference does not disclose the cited limitation "the feature quantity comparison means itinerantly shifts …." as seen in the argument section (see pg. 17, last paragraph – pg. 18, second paragraph). This argument is not considered persuasive since claim 20 is rejected by a new ground(s) of rejection under Schmid, with Roehrig and further in view of Hull and can be seen above in the rejection of the claim.

Applicant's arguments, see pg. 18, third paragraph, filed on 12/5/08, with respect to claims 5-7, 9, 10 have been fully considered and are persuasive. The rejection of claims 5-7, 9, 10 has been withdrawn.

Regarding claim 11, applicant argues that the Schmid reference does not disclose a feature quantity comparison ... generating a candidate-associated feature point pair having similar feature quantities (see pg. 18, last paragraph - pg. 19, second paragraph). This argument is not considered persuasive since the limitation is disclosed in section 4.2, 4.2.1, where model

Mk is defined by the vectors of invariants Vj calculated at the interest point of the model images; recognition consist of finding the model Mk which corresponds to a given query image I, that is the model which is most similar to this image; for this image, a set of vectors Vl is computed which corresponds to the extracted interest points; these vectors are then compared to the Vj of the based by computing: dM (Vl, Vj) = dl,j .... Examiner notes that the claim limitation only calls for a comparison of a feature point on the object with a model feature point and generating a point pair consisting of the points. This limitation is seen section 4.2, 4.2.1 where the calculation is executed and the pair is essentially the variables linked within the vector comparison.

Regarding claims 12-13, applicant argues that the claims are allowable due to the dependency from claim 11 (see pg. 19, second paragraph). This argument is not considered persuasive since claim 11 stands rejected and the arguments and rejection can be seen above.

Applicant's arguments, see pg. 19, second paragraph, filed on 12/5/08, with respect to claims 14, 15 have been fully considered and are persuasive. The rejection of claims 14, 15 has been withdrawn.

Regarding claim 21, applicant argues that the Schmid reference does not disclose a feature quantity comparison unit ... generating a candidate-associated feature point pair having similar feature quantities (see pg. 19, last paragraph – pg. 20, first paragraph). This argument is not considered persuasive since it is equivalent to the argument cited in claim 11. Applicant is directed to the arguments as cited above in claim 11.

Regarding claim 17, applicant argues that the Schmid reference does not disclose a feature quantity comparison unit ... generating a candidate-associated feature point pair having

similar feature quantities (see pg. 20, fourth paragraph). This argument is not considered persuasive since it is equivalent to the argument cited in claim 11. Applicant is directed to the arguments as cited above in claim 11.

Applicant's arguments with respect to claim 18 have been considered but are moot in view of the new ground(s) of rejection. Applicant argues that the Schmid reference does not disclose the cited limitation "the feature quantity comparison means itinerantly shifts ...." as seen in the argument section (see pg. 20, last paragraph – pg. 21, second paragraph). This argument is not considered persuasive since claim 18 is rejected by a new ground(s) of rejection under Watanabe, Schmid, with Roehrig and further in view of Hull and can be seen above in the rejection of the claim.

Regarding claim 19, applicant argues that the Schmid reference does not disclose a feature quantity comparison unit ... generating a candidate-associated feature point pair having similar feature quantities (see pg. 21, last paragraph - pg. 22, first paragraph). This argument is not considered persuasive since it is equivalent to the argument cited in claim 11. Applicant is directed to the arguments as cited above in claim 11.

Regarding claims 22, 23, applicant argues that the newly added claims are allowable due to the same reasons as cited in claim 21 (see pg. 22, third paragraph – last paragraph). This argument is not considered persuasive since claim 21 stands rejected and the arguments and rejection can be seen above in regards to claim 21. Furthermore, examiner notes that claim 22 stands rejected by Schmid and claim 23 is objected to as seen above.

Conclusion

12. Any inquiry concerning this communication or earlier communications from the examiner should be directed to EDWARD PARK whose telephone number is (571)270-1576. The examiner can normally be reached on M-F 10:30 - 20:00, (EST).

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Vikkram Bali can be reached on (571) 272-7415. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent Application Information Retrieval (PAIR) system. Status information for published applications may be obtained from either Private PAIR or Public PAIR. Status information for unpublished applications is available through Private PAIR only. For more information about the PAIR system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free). If you would like assistance from a USPTO Customer Service Representative or access to the automated information system, call 800-786-9199 (IN USA OR CANADA) or 571-272-1000.

Edward Park
Examiner
Art Unit 2624

/Edward Park/
Examiner, Art Unit 2624

/Vikkram Bali/
Supervisory Patent Examiner, Art Unit 2624